Chapter 1

PLANT PROPAGATION-INSPIRED ALGORITHMS

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Abstract

Plants represent some 99% of the eukaryotic biomass of the planet and have been highly successful in colonising many habitants with differing resource potential. The success of plants in earning a living suggests that they have evolved robust resource capture mechanisms and reproductive strategies. In spite of the preponderance of plant life, surprisingly little inspiration has been drawn from plant activities for the design of optimisation algorithms.

In this chapter we focus on one important aspect of plant activities, namely seed and plant dispersal. Mechanisms for seed and plant dispersal have evolved over time in order to create effective ways to disperse seeds into locations in which they can germinate and become established. These mechanisms are highly varied, ranging from morphological characteristics of seeds which can assist their aerial or animal-mediated dispersion, to co-evolved characteristics which reward animals or insects who disperse a plants seeds. At a conceptual level, dispersal can be considered as a search process, wherein the seed or plant is searching for good locations and therefore, inspiration from dispersal activities of plants can plausibly serve as the design inspiration for optimisation algorithms.

Initially, we provide an overview of relevant background on the seed dispersal process from drawing on the ecology literature. Then we describe a number of existing optimisation algorithms which draw inspiration from these processes, and finally we outline opportunities for future research.

1. Introduction

The key imperative of a plant's life is to maximise its number of viable offspring [11]. Many species of plants reproduce by producing seeds and then dispersing these in the landscape. The seeds are in essence embryonic plants, enclosed in a protective coat, usually with some stored food in order to provide energy for the germination process. The technical term for the dispersed unit is a *diaspore* and this may consist of a seed, spore or fruit containing seeds, plus any additional tissue which assists in dispersal. In this paper we employ the term seed in a board sense to encompass all of these cases.

If the seeds find a suitable location, they germinate and in turn reproduce themselves. Hence, the process of seed dispersal plays a critical role in ensuring the long-term success of a plant species and is the predominant process by which plants can 'move around' a landscape [18].

1.1. Dispersal Mechanisms

Plants make use use of multiple dispersal mechanisms, including:

1. wind dispersal,
2. animal dispersal,
3. water dispersal, and
4. ballistic dispersal.

Hence, dispersal mechanisms can be classed as abiotic (wind, water or gravity) or biotic (insect or animal dispersal). Many plants use more than one dispersal mechanism and dispersal can take place in stages. For example, wind dispersed seeds can subsequently be redispersed by ants or seed hoarding rodents.

Morphological adaptations in plants and seeds have arisen over time in order to increase the efficiency of seed dispersal. In the case of wind dispersal, seeds which have characteristics such as small size, wings, hairs etc. fall more slowly, essentially by lowering their wing loading (ratio of mass to surface area), and this promotes wider seed dispersal. Species with these adaptations are very common, comprising some 10-30% of all plants, and up to 70% of the flora in temperate plant communities [18]. Wind dispersed plants are common in dry habitants such as deserts [9]. An interesting example of this is provided by tumble weeds where the plant shoot dies and detaches from the root system. The seeds attached to the upper part of the plant are then dispersed as it is blown around the landscape. Some curious adaptations have emerged in order to promote the effectiveness of wind dispersal mechanisms whereby a plant manipulates its environment in order to ‘generate’ a local wind current in order to assist dispersal. One example is provided by the spores of ascomycete fungi where by synchronising the ejection of thousands of spores, the fungi create a flow of air that carries their spores further than they would otherwise disperse [37]. Another example is provided by oyster and shiitake mushrooms which release water vapour before releasing their spores which in turn cools the surrounding air creating convection currents thereby helping to disperse their spores [36].

Some curious adaptations have emerged in order to promote the effectiveness of wind dispersal mechanisms whereby a plant manipulates its environment in order to ‘generate’ a local wind current in order to assist dispersal. One example is provided by the spores of ascomycete fungi where by synchronising the ejection of thousands of spores, the fungi create a flow of air that carries their spores further than they would otherwise disperse [37]. Another example is provided by oyster and shiitake mushrooms which release water vapour before releasing their spores which in turn cools the surrounding air creating convection currents thereby helping to disperse their spores [36].

Adaptations for animal dispersal include the offering of ‘rewards’ for dispersion, such as fleshy, nutritious, fruits which attract the attention of frugivores (fruit eaters) who consume the fruit. The seeds contained in the fruit pass through the digestive tract of the animal and are eventually excreted back into the environment. This means of seed dispersal is common with some 50-75% of tree species in tropical forests producing fleshy fruits adapted for animal consumption [9]. A similar figure is quoted by [30] who notes that 75% of tropical tree species display adaptations for biotic seed dispersal. Other (non-reward) adaptations for animal dispersal include clinging structures such as hooks or resin whereby seeds stick to fur or feathers of animals and are accordingly dispersed as the animal moves around the environment (this mechanism led to the discovery of Velcro in 1948, inspired by the observation of seed burrs sticking to the hair of a dog [20]). Many types of animals are seed dispersers including various species of mammals, birds, bees, fish and reptiles [10, 30]. One example of such dispersal is provided by ants. It is estimated that more than 10,000 plant species have evolved mechanisms to assist dispersal of their seeds by ants [31]. Typically the ants are attracted using by an elaiosomes, or fleshy structure, attached to the seed which is rich in lipids and proteins. The elaiosome and attached seed is taken to the nest to feed larvae and the seed is then discarded and later germinates. Animals and insects can also play a role as secondary dispersers. For example, ants and dung beetles can transport seeds which have fallen from plants.

Apart from wind and animal dispersal, seeds can also be dispersed by water, for example via buoyant coconuts. Some plant species have evolved ballistic fruits that open explosively and can toss seeds several metres from the parent plant. In this chapter we employ the term seed in a board sense to encompass all of these cases.

1.2. Why Do Plants Disperse Their Seeds?

An obvious question given the wide range of strategies adopted by plants to disperse their seeds is what evolutionary advantages accrue to plants from their investment in dispersal structures? Such investments only make sense if dispersing seeds leads to a higher rate of seed survival and a higher rate of subsequent establishment. Three hypotheses are usually proposed to support the adaptive nature of seed dispersal [9], namely the:

1. escape hypothesis, the
2. colonisation hypothesis, and the
3. directed-dispersal hypothesis.

The core of the *escape hypothesis* is the claim that seeds which are dispersed further from their parent have higher rates of survival and reproductive success. In other words, if seeds were only dispersed in close proximity to their parent, their rates of mortality would be higher, due to density-dependent mortality factors such as insect / rodent predators which would be attracted to clusters of ‘target plants’, susceptibility to pathogen attack, and resource competition from other seedlings. Another factor which could promote dispersal is ‘shade escape’ as a non-dispersed seed would end up competing directly with their parent for light and other resources. In a study of 34 tree species, [1] found that seeds from species requiring light-gaps for early seedling survival had slower rates of descent, enhancing their chances of escape from the light shadow of their parent.

The *colonisation hypothesis* notes that habitats and environments change over time, and a currently resource poor environment may subsequently become more abundant. Hence, seeds which reach this environment, perhaps remaining dormant initially, will be well-placed to germinate and colonise the area if conditions later improve. This hypothesis underscores the fact that seed dispersal can be temporal as well as spatial, as some seeds can remain in a dormant condition for considerable periods awaiting better conditions. Dormancy capability is valuable, as it can notably increase the reproductive success of the parent plant [33].

The *directed dispersal hypothesis* [9] argues that plants can adapt their diaspores and / or their morphology in order to enhance their chances of dispersing seeds into locations which provide good conditions for seed establishment and growth. For example, plants can adapt their morphology in order to utilise differing seed dispersing agents. Non-random dispersal into resource rich environmental patches presents an obvious evolutionary advantage advantage over random seed dispersal methods [26, 32].

1.3. Design Trade-Offs

Plants can exert some control over their seed dispersal patterns as morphological factors such as plant height, fruit / seed size and design, and ease of abscission (release of fruit/seed) are all adaptable over time.

Taking plant height, a taller plant can produce a wider seed shadow via wind dispersal than a low-sized plant. Of course, a greater degree of tissue investment is required to grow a taller plant, leaving less energy for seed production, potentially creating a design trade-off.

In the case of seed design, plants can select different levels of investment in their seeds, with some plants adopting a ‘low investment’ model, where the plant invests little in individual seeds but produces a large number of them, with other plant species adopting a ‘high investment’ model, producing fewer, larger, seeds. A larger seed can contain greater energy reserves thereby enhancing the probability of germination but larger seeds are usually harder to disperse than smaller ones, requiring larger animals, stronger winds or more powerful propulsion mechanisms [34]. Hence, larger seed size will impact on the design of the plant’s dispersal mechanisms.

The level of investment in fruit production (for fruiting plants) can also be adapted as production of richer, more attractive, fruits will enhance biotic seed dispersal but at the expense of leaving less energy for other plant requirements.

In essence, when ‘selecting’ a dispersal mechanism, two costs are being balanced, the cost of seed mortality (arising when seeds produced by a plant fail to subsequently germinate), and the allocation costs (i.e. the costs of that dispersal mechanism. In summary, plants can employ a wide variety of seed dispersal techniques, each requiring different levels of resource investment, and each requiring differing plant morphologies which embed specific trade-offs.

1.4. Structure of Paper

The remainder of this chapter is organised as follows. Section 2. provides some background on aspects of the seed dispersal process Section 3. outlines a number of optimisation algorithms whose design has drawn inspiration from the plant propagation process. Conclusions and opportunities for future work are discussed in Section 5.

2. Background

As the seed dispersal pattern of plants is important both for individual and species-level survival, a significant research effort has been expended in order to gain insight into the dispersal patterns for various plant species. Levey et al (2008) [13] notes that the ‘Holy grail of seed dispersal is to accurately predict the probability distribution of seed density from a particular configuration of parents and then relate those distributions to seedling demography’ (p. 604).

The spatial distribution of seed dispersal from an individual plant, or cluster of plants, is known as a *seed shadow*. More formally, these seed shadows can be represented by a probability distribution, relating the probability that an individual seed is dispersed a given distance from its maternal plant. Spatial dispersal patterns can be considered either in one dimensional terms, focussing on dispersal distance, or in two dimensions by also considering the directionality of dispersion. Both dispersal distance and direction for an individual plant will be impacted by the nature of the plant's dispersal mechanism and by location-specific factors.

Ballists and ant-dispersed seeds tend to travel the shortest distances (up to a few metres typically), with wind-dispersal and animal dispersal producing greater dispersal distances in terms of both mode and maxima. Directional dispersal can be influenced by several factors, the most obvious of which is prevailing wind direction in the case of wind-dispersed seeds [34]. The directionality of animal dispersed seeds will be influenced by the topology of the local environment as this will impact on animal movement patterns.

A practical issue that arises in attempting to capture empirical data on seed dispersal is that long-range dispersal events tend to be under-reported as it becomes difficult to accurately attribute seeds to specific parent plants as seeds disperse over increasing distances. For example, extreme distance dispersal events, such as may occur when seeds get stuck to the feathers or feet of birds are unlikely to be captured in empirical studies. The problem of capturing good data on long-dispersal events is noted by many studies, with [5] pithily stating that 'for [dispersal] distances exceeding a few hundred metres we essentially know nothing'. However, there have been some attempts to construct general frameworks of long-distance dispersal [7] in order to facilitate the construction and testing of the biogeographical consequences of long-distance dispersal. Understanding long-distance dispersal of seeds is of critical importance in gaining insight into the spread of plant populations (including invasive species), and in explaining the diversity and dynamics of ecological communities [4].

Another perspective on seed dispersion is that it can be considered as taking place across time as well as spatially [7]. An obvious example is the case of long-distance dispersal whereby a seed or spore may be dispersed by rafting on ocean flotsam, and take many days to reach its final destination. More generally, seed germination and spore revival may be long delayed awaiting suitable environmental conditions and thus we can distinguish between seeds germinating from a *seed bank* (seeds dispersed in the past which have lain in the soil) and *seed rain* (recently deposited new seeds arising from current dispersal).

2.1. Modelling Seed Dispersal

Two main approaches have been taken to modelling of seed dispersal patterns, a conceptual approach which attempt to build a model from the underlying physical mechanisms of dispersal, and an empirical approach which seeks to reverse fit a mathematical model to real-world data.

In seeking to build a model of seed dispersal, [13] notes that an important distinction must be made between cases where the seeds are dispersed *abiotically*, for example by wind, and cases where seeds are dispersed *biotically*, for example, by animals or insects. In the former case, the focus is on parameterising a mechanistic seed dispersal model, accounting for plant height, characteristics of the seed structure, wind conditions etc. In the latter case, the situation is more complex, and it is necessary to consider factors governing animal movement, animal physiology, and animal behaviour. Initially thought to be infrequent, reports of such directed dispersal by animals are increasing, as more detailed studies of the food caching behaviours of animals are undertaken [35].

2.1.1. Modelling Wind Dispersal

The earliest studies which attempted to construct a model of wind borne dispersal of seeds used a ballistic formulation, considering seeds to be non-powered projectiles [8]:

$$x = \frac{Hu}{F} \tag{1}$$

where x is the predicted horizontal distance from maternal parent to the deposition site, H is seed release height above the ground, F is a constant descent velocity, and u is the horizontal wind velocity averaged between H and the ground. The basic ballistic model assumes that the dispersed seed reaches terminal velocity (the falling velocity of a seed in still air) immediately after release, and that horizontal wind velocity is constant during the descent phase.

Although this model is a simplification of reality, it highlights that there will be a variation in the deposition distance depending on the wind speeds in the downwind, crosswind and vertical directions, the terminal velocity of the seed, and its release height. For example, a low terminal velocity, such as would arise with a lightweight or an aerodynamic seed structure, will enhance dispersal distance as there is more chance of an uplift eddy with consequent horizontal displacement during the lengthier ‘descent’ process. The model also illustrates that the detachment mechanism from a plant is important as this determines the minimum level of wind speed which will act on the seed when it is detached from the plant.

A shortcoming of these models is that they produce seed dispersal estimates which have far lower maximum dispersal distances than are seen in the real world. A more realistic model can be obtained if variable windspeeds are incorporated, with turbulent fluctuations in the vertical velocity component. Simulations using these models produces dispersal distributions which are more realistic, producing maximum seed dispersal distances that are two to three orders of magnitude bigger than those produced by simple ballistic models. These distributions can be approximated by a power law dispersal kernel [18].

At a macro level, it may be possible to model long distance wind dispersal as storms, trade winds and high-altitude jet streams are at least partly predictable on longer time scales in terms of direction, time of year, and typical wind speeds [7].

2.1.2. Modelling Animal Dispersal

As animals are important seed dispersal vectors, knowledge of animal movement patterns and animal physiology could contribute to our understanding of seed dispersal distribution. Recent years have seen the development of the new multi-disciplinary field of *movement ecology* [29]. This field is concerned with empirical and theoretical study into the movement of animals, plants or microorganisms. Areas of interest include movement phenomena surrounding foraging and seasonal migration.

The simplest models of animal foraging movement ignore cognition and sensory inputs, corresponding to a case where resources are randomly dispersed and cognition and sensory capabilities are either non-existent or alternatively, too limited to effectively aid the search process. In this case, foraging movement can be modelled as being a random walk. The best-known random walk models assume Brownian motion and it was long thought that this could be used to approximate the diffusion of biological organisms. In turn, due to the Central Limit Theorem whereby the distribution of the sum of i.i.d. random variables with finite variance converges to a Gaussian, this would produce a normal distribution for multi-step foraging expeditions [29].

However, the assumption of Brownian motion ignores important aspects of real-world foraging including the ‘directional persistence’ typically exhibited by organisms. Animals rarely undertake 180 degree turns and revisit a just-sampled site. Animals also do not blindly move around the environment but rather stop when a resource is found, nor do they tend to persist in searching a ‘patch’ in the environment which has been unfruitful in the recent past.

Movements of animals might therefore be expected to display ‘fat tails’ having a greater number of very short and very long ‘jumps’ than would be expected under a Brownian motion assumption. When tested using empirical data from foraging organisms, the results indicate that, particularly in cases where resources are sparsely and randomly distributed, the foraging movements of many organisms are described as a Lévy flight, giving rise to the *Lévy flight foraging hypothesis* [28]. A Lévy flight is a random walk in which the step-lengths (jump sizes) have a power law distribution.

We may also consider a slightly move complex foraging model where resources are randomly distributed in the environment and the forager is allowed to have sensory perception, such as the ability to ‘see’ or ‘smell’ food resources and move accordingly. In this case, the animal behaves as follows [27]:

i. if there is a resource located within a direct vision distance r_v then the searcher detects it with certain probability and moves on a straight line to the detected resource;

ii. if there is no detected resource within distance r_v then the searcher chooses a direction at random and a distance l_j from a probability distribution and moves incrementally to the new point constantly looking for resources within a distance r_v along the way;

iii. if it does not detect any resources, it stops after traversing distance l_j and chooses a new direction and distance l_{j+1}, otherwise it moves to the resource;

where the probability distribution for move distances is a Lévy distribution, as follows:

$$P(l_j) \sim l_j^{-\mu} \tag{2}$$

Analysis in [27] suggests that in the absence of a priori knowledge of the distribution of food resources, the optimal strategy for a forager is to choose $\mu \approx 2$. The study notes that several empirical studies of foraging behaviour across a range of organisms (micro organisms, insects, birds, mammals) have been found to follow a Lévy distribution of flight lengths or times with $\mu \approx 2$.

Although the above analysis ignores a number of important issues concerning real-world foraging movement such as personal and social learning, environments in which resources are patchy, and local environment topology, it provides some support for a claim that the foraging movement patterns of animals will produce a leptokurtic pattern of seed dispersal.

An additional physiological factor in animal-mediated dispersal is the length of time the seed is carried by the animal before dispersal. Some animals such as birds will typically excrete ingested seeds within a few hours of consumption, in other cases, the digestion passage time may be considerably longer, 3-17 days in the case of some species of tortoises [10]. Seed morality may also vary depending on the animal that ingests them, although in the case of tortoises, less than 5% of seeds were found to be damaged whilst in transit through the digestive tract [10].

Animal-mediated seed dispersal is a complex animal-plant interaction which can take multiple forms, including cases where seeds commence germination whilst in the digestive tract of an animal. Other examples include the caching of seeds by animals in areas suitable for seed establishment and survival. Initially, thought to be infrequent, reports of such directed dispersal by animals are increasing, as more detailed studies of the food caching behaviours of animals are undertaken [35]. Examples include cases where animals cache seeds in areas of suitable soil conditions for seed growth, and caching of seeds at an optimal depth for their survival. Such synergistic interactions are plausible, as an ecology in which both plants and animals thrive is beneficial to both.

The social environment of animals also impacts on seed dispersal. Some mammals and birds live in groups, and hence defecate collectively at their feeding and resting sites. In turn, this will result in more localised dispersal of seeds than would occur if the seed consumers were solitary.

Due to the number of relevant factors, and our imperfect understanding of animal behaviours, is clear that developing a comprehensive model of animal movements, which could then feed into a model of animal-mediated seed dispersal, is a non-trivial task. However, we can expect to see continued attempts to develop such models as the field of movement ecology develops.

2.2. Modelling

2.2.1. Empirical Modelling

An alternative approach to the modelling of seed dispersal patterns is to concentrate on empirical data rather than attempting to construct an explanatory model using underlying physical mechanisms. Empirical examination of the relationship between the number of seeds dispersed and distance from parent plant, indicates a leptokurtic distribution, displaying a higher peak and a heavier tail than a Gaussian distribution, with seed numbers decreasing monotonically with distance from the parent plant [9, 19, 34]. In attempting to reverse engineer a seed distribution function from observed seed count data, the aim is to uncover a probability density function $p(x)$ which gives the probability that a dispersed seed arrives at a distance x away from the source plant. This defines a dispersal kernel which maps seed density to distance (one dimensional case), or seed density by unit area to distance (two dimensional case) [18]. Typical kernels seen in the literature are Gaussian, negative exponential, and the inverse power function. A negative exponential model will have the general form [3]:

$$S_D = a_1 \cdot exp(-b_1 \cdot D) \tag{3}$$

where S_D is the density of seeds at distance D from the source and a_1 and b_1 are constants indicating the density of seeds falling at the source and the slope of the decline in seed density with distance. In contrast, an inverse power model produces longer, fatter, tails:

$$S_D = a_2 \cdot (D)^{-b_2} \tag{4}$$

Based on sample of 73 herbaceous species and 75 tree/shrub samples [33] indicates that a negative exponential distribution provides a reasonable fit to the data, noting that the fit was better for the part of the curve around the mode with the tail area being less well-explained by this distribution. The study also noted that many empirical investigations stop collecting data on seed dispersal long before the end of the right tail and hence, their results need to be read with caution.

Differing studies have examined the seed dispersal patterns of numerous plant species and these have have produced varying suggestions as to whether a negative exponential or an inverse power model (negative power distribution) produces a better fit to the collected data [26] . The relative scarcity of data on long-range dispersal of seeds can make it difficult to distinguish between alternative model specifications.

In an attempt to better explain the tail of dispersal curves, some authors including [3] have suggested the use of a mixed model formulation with two kernel components: with a fat-tailed kernel for long distance dispersal, and negative-exponential component for short-distance dispersal:

$$S_D = a_3 \cdot exp(-b_3 \cdot D) + (c_3 \cdot D)^{-p_3} \tag{5}$$

As distance from the parent plant increases, the first component goes to zero and the second component then estimates the tail.

One interesting question is whether the ‘typical’ tail shape of the dispersal curve is qualitatively impacted by the mode of dispersal, in other words, do certain dispersal mechanisms produce a significantly different tail to the dispersal curve? Based on a study employing 68 different datasets, [34] indicates that there is no clear link between tail shape and dispersal mode, suggesting that there is relatively little selection pressure for tail behaviour.

A further complicating factor is that the seeds of most plants are dispersed by multiple mechanisms. Hence, their seed shadows are comprised of a mixture of dispersal models [17], hence, the calibration of a seed distribution pattern to a single model is likely to be errorful. An additional feature is that dispersal agents may engage in secondary dispersal, i.e. from initial dispersal sites, thereby increasing the seed shadow.

2.3. Plant-inspired Algorithms

Until recently, little attention was paid to the potential utility of plant metaphors for the design of computational algorithms. The last few years have seen increased interest in this area, with the development of a number of plant-inspired algorithms. Broadly speaking, these fall into three categories, namely algorithms inspired by:

i. plant propagation behaviour,

ii. light-foraging behaviour (branching algorithms), and

iii. purported swarm behaviour of plant root networks.

In this paper we restrict attention to the first of these.

3. Plant Propagation Algorithms

Plants have a repertoire of processes by which they propagate themselves including seed dispersal and root propagation. Effective propagation plays an important role in ensuring the survival of plant species, and in turn this depends on the ability of the plant to propagate itself into resource-rich areas. Hence,this process can metaphorically provide inspiration for the design of robust optimisation algorithms and also for the design of engineering systems [20].

Three algorithms which have been inspired by these processes, the *Invasive Weed Algorithm* [15], the *Paddy Field Algorithm* [21] and the *Strawberry Plant Algorithm* [24] are discussed below.

3.1. Invasive Weed Optimisation Algorithm

The *invasive weed optimisation algorithm* (IWO) (pseudocode provided in Algorithm 2), based on the colonisation behaviour of weeds, was proposed by Mehrabian and Lucas in 2006 [15]. The inspiration for the algorithm arose from the observation that weeds, or more generally, any plant, can effectively colonise a territory unless their growth is carefully controlled. Two aspects of this colonising behaviour are that weeds thrive in fertile soil and reproduce more effectively than their peers in less-fertile soil, and the dispersal of seeds during plant reproduction is stochastic.

Algorithm 1: Invasive Weed Algorithm [15]

```
Generate $p_{initial}$ seeds and disperse them randomly in the search space;
Determine the best solution in the current colony and store this location;
repeat
    Each plant in the population produces a quantity of seeds depending on the quality of its location;
    Disperse these new seeds spatially in the search space giving rise to new plants;
    If maximum number of plants ($p_{max} > p_{initial}$) has been exceeded, reduce the population size to $p_{max}$ by eliminating the weakest (least fit) plants. This simulates competition for resources;
    Assess the fitness of new plant locations and, if necessary, update the best location found so far;
until until terminating condition ;
Output the best location found;
```

The three key components of the algorithm are seeding (reproduction), seed dispersal and competition between plants. Mehrabian and Lucas operationalised these mechanisms in the following way in the IWO algorithm.

3.1.1. Seed Production

Each plant produces multiple seeds, based on its fitness relative to that of the other plants in the current colony of weeds. A linear scaling system is used whereby all plants are

Algorithm 2: Invasive Weed Algorithm

```
Generate $p_{\text{initial}}$ seeds and disperse them randomly in the search space;
Determine the best solution in the current colony and store this location;
repeat
    Each plant in the population produces a quantity of seeds depending on the quality of its location;
    Disperse these new seeds spatially in the search space giving rise to new plants;
    If maximum number of plants $p_{\max} > p_{\text{initial}}$ has been exceeded, reduce the population size to
    $p_{\max}$ by eliminating the weakest (least fit) plants. This simulates competition for resources;
    Assess the fitness of new plant locations and, if necessary, update the best location found so far;
until terminating condition ;
Output the best location found;
```

guaranteed to produce a minimum number of seeds (min_{seeds}), and no plant can produce more than a maximum number of seeds (max_{seeds}). The number of seeds produced by an individual plant is calculated using the following:

$$s(x) = \frac{f(x) - f_{\min}}{f_{\max} - f_{\min}} * (s_{\max} - s_{\min}) + s_{\min} \tag{6}$$

where $f_{\max}$ and $f_{\min}$ are the maximum and minimum fitnesses in the current population and $f(x)$ is the fitness of the plant x.

3.1.2. Seed Dispersal

While the IWO algorithm employs the notions of fitness and reproduction, unlike the GA, the IWO does not use genetic operators in the creation of populational diversity. Exploration of the search space is obtained via a simulated seed dispersal mechanism. The seeds associated with each plant are dispersed by generating a random displacement vector and applying this to the location of their parent plant. The displacement vector has n elements corresponding to the n dimensions of the search space, and is obtained by generating n normally distributed random numbers, with a mean of zero and a standard deviation calculated using the following:

$$\sigma_{iter} = \left(\frac{iter_{max} - iter}{iter_{max}}\right)^{n} (\sigma_{max} - \sigma_{min}) + \sigma_{min} \tag{7}$$

where $iter$ is the current algorithm iteration number, $iter_{max}$ is the maximum number of iterations, σ_{max} and σ_{min} are maximum and minimum allowable values for the standard deviation, n is a non-linear modulation index, and σ_{iter} is the standard deviation used in the current iteration in calculating the seed displacements.

The effect of this formulation is to encourage random seed dispersal around the location of the parent plant, with decreasing variance over time. This results in greater seed dispersal in earlier iterations of the algorithm, promoting exploration of the search space. Later, the balance is tilted towards exploitation as the value of σ_{iter} is reduced. The incorporation of the non-linear modulation index in (7) also tilts the balance from exploration to exploitation as the algorithm runs.

Depending on the scaling of the search space, the same value of σ_{iter} could be applied when randomly drawing each element of the displacement vector. Alternatively, differing values of $\sigma_{initial}$ and σ_{final} could be set for each dimension if required.

3.1.3. Competition for Resources

Competition between plants is simulated by placing a population size limit on the colony (p_{max}). The plant colony starts with a population of size $p_{initial}$. The population increases as new plants grow in subsequent generations. Once the p_{max} population limit is reached, parent plants compete with their children for survival. The parent and child plants are ranked by fitness, with only p_{max} plants surviving into the next generation. This mechanism ensures that the best solution found to date cannot be lost between iterations (elitism).

3.1.4. Performance of the Algorithm

The IWO is a conceptually simple, numerical, non-gradient based, optimisation algorithm. As yet due to its novelty, there has been limited investigation of its effectiveness, scalability and efficiency. Mehrabian and Lucas [15] report GA and PSO competitive results from the IWO algorithm with settings of 10-20 weeds, maximum and minimum numbers of seeds per plant of 2 and 0 respectively, and a non-linear modulation index value of 3. Competitive results for the IWO algorithm are also reported by [2, 16] and [38].

The algorithm requires that several problem-specific parameters are set by the modeller including, the maximum and minimum number of seeds that a plant can produce, the values for σ_{max}, σ_{min} and $iter_{max}$, and the initial and the maximum population size. However, the determination of good values for these parameters is not necessarily a trivial task, particularly in poorly understood problem environments.

Recent work has extended the application of IWO into clustering where each individual seed consists of a string of up to n real-valued vectors of dimension d, corresponding to the n cluster centre coordinates (in d dimensional space) [14]. Apart from the IWO algorithm, a number of other algorithms which draw inspiration from seed-dispersal behaviour have been proposed, including the *Paddy Field Algorithm* [21].

3.2. Paddy Field Algorithm

The *paddy field algorithm* was first proposed by Premaratne, Samarabandu and Sidu (2009) [21]. This algorithm draws inspiration from aspects of the plant reproduction cycle, concentrating on the processes of pollination and seed dispersal.

Let the vector $x = (x_1, x_2, \ldots, x_n)$ correspond to a location in an n dimensional space and $y = f(x)$ is the 'fitness' or 'quality' of that location. Each seed i therefore, has a corresponding location x_i and a corresponding fitness. The paddy field algorithm manipulates a population of these 'seeds' in an attempt to find a good solution to the optimisation problem of interest. The algorithm consists of five stages, sowing, selection, seeding, pollination, and dispersion [21]. Each of these are described below.

3.2.1. Sowing

An initial population of (p) seeds are (sown) at random locations in the search space.

3.2.2. Selection

The seeds are assumed to grow into plants, and each of these plants has an associated fitness value (y) determined by the output of the underlying objective function when evaluated at the plant's location. The plants are ranked by fitness, and the best n plants are then selected to produce seeds.

3.2.3. Seeding

Each plant produces a number of seeds in proportion to its fitness. The fittest plant produces s_{max} seeds and the other plants produces varying amounts of seeds, calculated using:

$$s = s_{max} \frac{y - y_t}{y_{max} - y_t}$$

The term y_{max} is the fitness of the best plant in the current population, and y_t is the fitness of the lowest ranked plant selected in the previous step. Although the algorithm describes this step as 'seeding', it can more correctly be considered as the process of growth of flower structures in order to enable pollination.

3.2.4. Pollination

Only a portion of the seeds become viable and to determine this portion, a simulated pollination process is applied whereby the probability that a seed is pollinated depends on the local density of plants around the seed's parent plant. The higher the density, the greater the chance of pollination. A hypersphere of radius a is defined, and two plants are considered to be neighbours if the distance between them is less than a. The pollination factor U_j of plant j (with $0 \leq U_j \leq 1$) is then calculated using:

$$U_j = \exp(v_j / v_{\max} - 1)$$

where v_j is the number of neighbours of the plant j and $v_{\max}$ is the number of neighbours of the plant with the largest number of neighbours in the population.

3.2.5. Dispersion

The pollinated seeds are then dispersed from the location of their parent plant such that the location of the new plant (grown from the dispersed seed) is determined using $N(x_j, \sigma)$ where x_j is the location of the parent plant and σ is a user-selected parameter.

The above five steps are iterated until a termination condition is reached. In summary, the fittest plants give rise to the greatest number of seeds, and search is intensified around the better regions of the landscape uncovered thus far. Variants on the PFA include [12].

Algorithm 3: Paddy Field Algorithm [21]

```
Generate an initial population of $p$ plants each located randomly in the search space;
Choose value for $maxiter$ and $n$ (see below);
Set generation counter $iter = 1$;
repeat
    Calculate fitness of each plant ($y_i$) and store in vector $N$ ($N_i = fitness(y_i : i = 1, \dots, p)$);
    Sort $N : (N_i : i = 1, \dots, p)$ into descending order (assuming the objective is to maximise fitness);
    for $i = 1 : n$ (top n plants) do
        Generate seeds for each selected plant;
        Implement pollination step;
        Disperse pollinated seeds;
    end
    Replace old population with new plants;
    iter = iter+1;
until $iter = maxiter$ ;
Output the best location found;
```

3.3. Strawberry Plant Algorithm

Although many plants propagate using seeds, some employ a system of ‘runners’, or horizontal stems which grow outwards from the base of the plant. At variable distances from the parent plant, if suitable soil conditions are found, new roots will grow from the runner and in turn produce an offspring clone of the parent plant. An example of this behaviour is provided by modern strawberry plants which can propagate via seeds and by runners. This has inspired the development of an optimisation algorithm based on this phenomenon [24]. The algorithm is based on the following ideas:

- healthy plants in good resource locations generate more runners,
- plants in good resource locations tend to send short runners in order to exploit local resources,
- plants in poorer resource locations tend to send longer runners to search for better conditions, and
- as the generation of longer runners requires more resource investment, plants generating these will create relatively few of them.

The algorithm therefore seeks to balance exploration with exploitation, with increasing local exploration over time as plants concentrate in the locations with best conditions for growth. Salhi and Fraga [24] report competitive results from this algorithm when applied to a number of real-valued benchmark optimisation problems. Algorithm 4 presents an adapted version of the algorithm based on [24].

4. Applications

Despite the relative recency of the introduction of plant propagation-inspired algorithms, there have been a number of applications to a range of diverse real-world problems,

Algorithm 4: Strawberry Propagation Algorithm (adapted from [24])

```
Generate an initial population of $m$ plants $p_i : i = 1, \dots, m$ each located randomly in the search space;
Choose values for $maxgen$ and $y$ (see below);
Set generation counter $gen = 1$;
repeat
    Calculate fitness of each plant and store in vector $N$ $(N_i = fitness(p_i : i = 1, \dots, m))$;
    Sort $N : (N_i : i = 1, \dots, m)$ into descending order (assuming the objective is to maximise fitness);
    for $i = 1 : (m/10)$ (top 10% of plants) do
        Generate $(y/i)$ short runners for each plant ($y$ is a user-defined parameter which defines the intensity of local search around each of the fitter plants);
        if any of the new locations has higher fitness than that of the parent plant then
            move the parent plant to the new location with the highest fitness $(r_i \rightarrow p_i)$;
        else
            Discard the new locations and the parent plant stays at its current location;
        end
    end
    for $i = (m/10) + 1 : m$ (indices for remaining plants) do
        Generate one long runner for each plant not in the top 10% and select the location of the end-point $r_i$ for that runner randomly in the search space;
        if the new location has higher fitness than that of the parent plant then
            move the parent plant to the new location $(r_i \rightarrow p_i)$;
        else
            Discard the new location and the parent plant stays at its current location;
        end
    end
until $gen = maxgen$ ;
Output the best location found;
```

showing promise compared to existing approaches. We mention a selection of applications here: these applications range from recommender systems [38] to engineering problems [39, 40]. [39] apply the Invasive Weed Optimisation algorithm to the problem of optimising radio antenna structures. They find that the Invasive Weed Optimisation is competitive with the Particle Swarm Optimisation (PSO) algorithm, in accuracy, speed of convergence and simplicity. [41] apply a modified (discrete) invasive weed optimization algorithm to optimize DNA encoding sequences. Experimental results show that the proposed method is effective and convenient for the design and selection of effective DNA sequences in silico for controllable DNA computing.

[42] use a discrete invasive weed optimization (DIWO) algorithm for cooperative multiple task assignment of unmanned aerial vehicles (UAVs) and compare the solutions with those of genetic algorithms (GAs). Their results show that DIWO has better performance than GAs in both optimality of the solutions and computation time.

[40] examine the performance of their extended Strawberry Propagation Algorithm on a range of constrained engineering optimisation problems on continuous domains, including design of welded beam, pressure vessel, spring and speed reducer. Their results are that the Strawberry Propagation Algorithm found either near best known solutions or optimal ones to all problems. They compare the Strawberry Propagation Algorithm results to results obtained with other approaches such as GAs, Fogel's Evolutionary Programming, PSO, variations of the Harmony Search Algorithm and Integer Programming, and find that the

Strawberry Propagation Algorithm is superior in the majority of cases.

5. Conclusion

At a conceptual level, plant dispersal can be considered as a search process, wherein the seed or plant is searching for good locations and therefore, inspiration from dispersal activities of plants can plausibly serve as the design inspiration for optimisation algorithms. In this chapter we focussed on different processes of plant dispersal, and described a number of existing optimisation algorithms which draw inspiration from these. These were the *invasive weed optimisation* algorithm, the *paddy field* algorithm, and the *strawberry plant* algorithm.

In this work, we have noted and justified an array of plant behaviours which are exhibited in the natural world. With some exceptions, little inspiration has been taken from these mechanisms, as yet, for the design of computational algorithms. Most of the algorithms developed thus far are relatively recent in design and further work is required in order to assess their utility and to assess more fully whether they represent truly novel problem-solving mechanisms or whether they are qualitatively similar to existing natural computing algorithms. Work to date appears to indicate that they are at least competitive on the problems to which they have been applied. However, there is clearly rich potential for future work.

We wish to stimulate interest in this exciting, and under-explored are of natural computing. Of great importance here are the investigation of additional strategies for overcoming local optimality in complex solution spaces, and performing a robust search of a solution space. Additional research should study the degree to which neighbourhoods are exploited under different parameter settings governing the operation of each algorithm.

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